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# Uncertainty-averse TRANSCO planning for accommodating renewable energy in $CO_2$ reduction environment

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**Abstract** The concern of the environment and energy sustainability requests a crucial target of $CO_2$ abatement and results in a relatively high penetration of renewable energy generation in the transmission system. For maintaining system reliability and security, the transmission company (TRANSCO) has to make strategic planning to handle the uncertainty challenges from the intermittent renewable energy resources. In this paper, a stochastic multi-period multi-objective transmission planning (MPMOTP) model is proposed to reduce correlated uncertainties from renewable energy generation, conventional generation, demand-side variations, market price volatility, and transmission configuration. Three objectives, i.e. social $CO_2$ reduction benefit, energy purchase and network expansion cost and power delivery profit, are optimized simultaneously by a developed two-phase multi-objective particle swarm optimization (MOPSO) method. The feasibility and effectiveness of the proposed uncertainty-averse MPMOTP model have been verified by the IEEE 24-bus test system.

**Keywords** $CO_2$ reduction, Renewable energy, Uncertainty, Multi-objective planning, TRANSCO, MOPSO

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## 1 Introduction

The theme of energy sustainable development and conservations is widely recognized around the world, while the electric power industry is regarded as the major $CO_2$ emission sector with the traditional fossil-dependent production. In the deregulated environment, $CO_2$ reduction has already become the most significant concern involved in the decision making process within the multi-layer architecture of electricity generation, trading, transmission and distribution, even in the retail aspect, respectively dominated by generation companies (GENCOs), market operator (MO), transmission companies (TRANSCOs), distribution companies (DISCOs) and retailers.

From the last decade, numerous literatures and projects have already been carried out to demonstrate the feasible solutions to reduce $CO_2$ emission, which can be categorized into three schemes, i.e. technological $CO_2$ abatement, market-oriented based $CO_2$ trading and alternative energy production. As firstly discussed in [1] and further investigated in [2], on perspective of GENCOs and power system operation, $CO_2$ capture and storage (CCS) is addressed as a most promising technology for $CO_2$ reduction. On basis of the low-carbon economy analysis in [3], for the conscious of the economic factors in day-ahead energy market and cap-and-trade carbon emission market, a flexible operation model is proposed in [4] to trade off the maximum profit with adaptive carbon emission for a generating unit combining with proper coordination of generation schedule, CCS schedule and market bidding strategies. Alternative energy production could be highly efficient energy resources or more environmental energy conversions, in which renewable energy is leading this role for $CO_2$ mitigation from the current to the future, a huge amount of wind and photovoltaic (PV) energy will widespread in the transmission system to replace the conventional generation, as reviewed in [5].

However, the intermittent characteristics of the diverse renewable energies will derive huge uncertainties to the transmission system operation. Therefore, a strategic uncertainty-averse TRANSCO planning is necessary to ensure the adequacy and reliability of the power system operation for accommodating renewable energy in $CO_2$ reduction environment.

Various approaches for handling uncertainties in transmission planning process have been summarized in [6]. In [7], the market uncertainties are identified as possible future scenarios solved by the mixed integer linear programming (MILP) on a flexible transmission planning model, and assessed with reliability and security criterions referring to the indices of expected energy not supplied (EENS), expected cost of interruptions (ECOST), and interrupted energy assessment rate (IEAR) [8]. Subsequently, a stochastic MILP approach complemented with risk aversion was proposed in [9]. Furthermore, to assess the robustness of expansion plans, a Brazil test grid is presented [10] to illustrate the stochastic approach is more suitable than the traditional deterministic method. Additionally, a stochastic multi-objective optimization framework is proposed in [11] to take security constrains into concern for transmission planning. In the other perspectives, a congestion surplus [12] is identified in a multi-objective transmission planning (MOTP) model for dealing with the risk of the network congestions. Recently, for integrating the large-scale wind power, a probabilistic MOTP model equipped with risk-control strategies is developed by [13] to avoid transmission overloading. Extensive uncertainty studies are allocated in [14] and [15] to conduct the distributed energy resources (DERs) impacts on distribution systems.

Till now, the uncertainties faced by the TRANSCO are normally considered as independent factors, however, immersed in the future smart grid surroundings, as a profit chasing commercial player, an extra pressure for the TRANSCO is to fully understand the high correlations among these uncertainty diversities hidden in the transmission planning process to flexibly balance the intermittent recourses and stochastic consumptions.

In this paper, the wind power and PV energy are selected to represent the renewable energy caused uncertainties. The effort of demand response (DR) is concerned in the demand side to intensify the consumption behavior. To assess the circumvent uncertainties in terms of the output of wind and PV generating units, demand response related load fluctuation, conventional generation units, market price volatility, and transmission path deployment, the correlation coefficient matrix is introduced to handle the dependency of the uncertainties in the paper. A stochastic MPMOTP model is proposed for this uncertainty-averse TRANSCO planning, incorporated with the following objectives: 1) maximize the social benefit via $CO_2$ reduction, 2) minimize the TRANSCO cost of energy purchase and network expansion, 3) maximize the profit of power delivery. A two-phase MOPSO schema is employed to be the solver. The application of the proposed MPMOTP model is demonstrated on the IEEE 24-bus testing system to show its feasibility.

## 2 Modeling of uncertainties

Aiming to fulfill the critical target of $CO_2$ reduction, in energy purchase and transmission processes, the TRANSCO has the natural attribute to take reactions to hedge the uncertainties associated with the government policy and the huge amount of renewable energy integration. The proper planning strategy can help the TRANSCO to maintain the power systems operated in an economic efficient and secure condition, constrained by various new uncertainty boundaries. In this paper, various uncertainties are taken into concerns, i.e. renewable energy generation (wind and PV), demand-side variations, conventional units' production, market factor, and transmission path configuration. Precisely, the correlation characteristics of these uncertainties are taken into account and formulated as follows.

### 2.1 Correlation of uncertainties

The indication of stochastic variables for wind, PV, facilities configuration and demand identification can be seen as uncertain factors according to the forecast deviations, the measurement errors, the unpredictable system contingencies or the electricity market price volatilities. Therefore, the probabilistic analysis is the proper approach to handle the variations of these uncertainties. However, the uncertainty variables could be dependent to each other, e.g. the weather conditions can impact wind/PV generation and household consumption, simultaneously. Hence, in this work, the correlation coefficient matrix is used to illustrate the considerable dependency of the uncertainty variables. To define the degree of the dependence among variables, each correlation coefficient should be assigned in [−1, 1], where −1 and 1 indicate the perfect positive and negative relationship between the related variables.

As described in [16], the correlation coefficient $\boldsymbol{\varphi}_{\boldsymbol{X},\boldsymbol{Y}}$ between two uncertainty variables $\boldsymbol{X}$ and $\boldsymbol{Y}$ can be expressed as

$$\boldsymbol{\varphi}_{X,Y} = \frac{E[(\boldsymbol{X}-\boldsymbol{\mu}_X)(\boldsymbol{Y}-\boldsymbol{\mu}_Y)]}{\boldsymbol{\sigma}_X\boldsymbol{\sigma}_Y} \tag{1}$$

where $E$ represents the expected value operator; $(\boldsymbol{\mu}_X, \boldsymbol{\mu}_Y)$ and $(\boldsymbol{\sigma}_X, \boldsymbol{\sigma}_Y)$ are the expected value and standard deviations of $\boldsymbol{X}$ and $\boldsymbol{Y}$.

Once the probability density function (PDF) of each uncertainty variable is addressed, the correlation coefficient matrix $\boldsymbol{C}$ can be obtained,

$$\boldsymbol{C} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \dots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \dots & \varphi_{2n} \\ \vdots & \vdots & & \vdots \\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn} \end{bmatrix} \tag{2}$$

correspondingly, the refined uncertainty variable can be re-denoted as $\boldsymbol{Z}$ with the expression

$$\boldsymbol{Z} = \boldsymbol{H} + \boldsymbol{C}\widetilde{\boldsymbol{X}} \tag{3}$$

where $\widetilde{\boldsymbol{X}}$ is the forecasted values of uncertainty variables, such as wind power or PV output; $\boldsymbol{H}$ represents the initial value of these variables, which can be achieved from the historical data.

### 2.2 Wind energy uncertainty

The wind energy is converted from wind speed and behaved with the fluctuating and stochastic characteristics. As discussed in [17], the wind speed is normally followed a Weibull distribution, the PDF function is adopted to the wind variations, following

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \mathrm{e}^{-\left(\frac{v}{c}\right)^k} \tag{4}$$

where $v$, $k$ and $c$ are respectively represent the wind speed, shape factor and scale factor, $k > 0$, $v > 0$ and $c > 1$.

Then, the wind power output can be formulated as

$$P_w = \begin{cases} 0 & 0 \le v < V_{ci} \\ \overline{P_w}(A + Bv + Cv^2) & V_{ci} \le v < V_r \\ \overline{P_w} & V_r \le v < V_{co} \\ 0 & v \ge V_{co} \end{cases} \tag{5}$$

where the parameters of $A$, $B$ and $C$ can be defined in [17]; $V_{ci}$, $V_r$ and $V_{co}$ are the cut-in wind speed, rated wind speed and cut-out wind speed, respectively; $\overline{P_w}$ is the rated power of a wind unit.

### 2.3 PV energy uncertainty

The production of PV unit is dominated by the illumination intensity, a number of investigations have shown the PDF of solar radiation is following the Beta distribution [18],

$$f(R) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{R}{R^{\max}}\right)^{\alpha-1}\left(\frac{R}{R^{\max}}\right)^{\beta-1} \tag{6}$$

where $\Gamma$ is the Gamma function; $\alpha$ and $\beta$ are the shape parameters; $R$ is the illumination intensity with the maximum value of $R^{\max}$.

The relationship between the illumination intensity and the output of a PV unit can be described as [18]

$$P_s = \begin{cases} \overline{P_s}\left(\frac{R}{R_r}\right) & 0 \le R \le R_r \\ \overline{P_s} & R > R_r \end{cases} \tag{7}$$

where $R$ is the illumination intensity with the rated value $R_r$ and $\overline{P_s}$ is the rated output power of the solar unit.

### 2.4 Conventional energy uncertainty

For the conventional generation unit, considering the capacity expansion or withdrawal, the unit output can be defined as the chance constrained probability distribution,

$$\Pr\left(P_{gi} - \overline{P_{gi}} \le 0\right) \ge \gamma_i \tag{8}$$

where $P_{gi}$ is the possible value of conventional generation at $i^{\text{th}}$ bus with the maximal capacity limitation $\overline{P_{gi}}$ and quantified by a specified probability $\gamma_i$.

### 2.5 Market price uncertainty

Since the electricity price could vary in multiple planning periods, the forecasted locational marginal pricing (LMP) of $i^{\text{th}}$ bus can be adopted to meet the predicted demand, and denoted as $\lambda_i$. The LMP is assumed to follow the discrete probability distribution,

$$\Pr(C_{\text{LMP}} = \lambda_i) = \varepsilon\zeta_i \tag{9}$$

where $C_{\text{LMP}}$ is the value of LMP; $\zeta_i$ is the occurrence probability of $\lambda_i$ and $\varepsilon$ is a random variable represents the possible volatility of LMP, while $\varepsilon$ is within the boundary of [0.9, 1.1], $\sum\zeta_i = 1$, $i = (1, 2,\ldots, N_{\text{LMP}})$.

### 2.6 Demand-side uncertainty

The fast growth of smart grid and intelligent control technology will offer a good opportunity to apply DR and flexible consumption in the demand side. Therefore, the uncertainty can be decomposed to be two portions, i.e. DR and load variation.

In this work, the active DR is assumed to be with the price-driven scheme. A Gaussian distribution is applied to describe the effect of the elastic demand, which is bounded by the maximum and minimum credible values [19],

$$f(\varsigma) = \begin{cases} 0 & \varsigma < \varsigma^{\min} \\ \frac{1}{\sqrt{2\pi}\sigma_d}\mathrm{e}^{-\left[(\varsigma-\mu_d)/\sqrt{2}\sigma_d\right]^2} & \varsigma^{\min} \le \varsigma \le \varsigma^{\max} \\ 0 & \varsigma > \varsigma^{\max} \end{cases} \tag{10}$$

where $\sigma_d$ and $\mu_d$ represent the standard deviation and mean value of the demand elasticity $\varsigma$, which responds to $\lambda_i$, and the volume of DR can be formulated as

$$P_{ei} = \overline{P_{ei}} \frac{\varsigma\left(\lambda_i - \overline{\lambda_i}\right)}{\overline{\lambda_i}} \tag{11}$$

where $\overline{P_{ei}}$ is the settled initial value of the elastic demand and $\overline{\lambda_i}$ is the fixed price on basis of the historical archive.

In addition, according to the predicted demand $\overline{P_{li}}$, the load variation $\widetilde{P_{li}}$ at $i^{\text{th}}$ bus is imposed to follow the normal distribution $N\left(\mu_i, \sigma_i^2\right)$ for exhibiting the uncertainty of the natural load growth. Here, $\mu_i$ is the expectation of the forecast load and $\sigma_i$ is the standard deviation.

Eventually, the assembled demand yielded in this paper can be given by

$$P_{di} = \overline{P_{li}} + \widetilde{P_{li}} - P_{ei} \tag{12}$$

### 2.7 Transmission line uncertainty

Typically, the availability of the existing and candidate transmission lines can utilize the (0–1) distribution to represent the line uncertainty, where 0 indicates the line is in failure (or maintenance) status, while 1 shows the line is in the normal operating state.

## 3 Uncertainty-averse TRANSCO planning

### 3.1 Uncertainty characterization

For properly addressing the uncertainties mentioned above in the TRANSCO planning progress, the scenario-based stochastic programming approach is employed here to handle the issued uncertain conditions. A scenario is a sequence of time-based transmission system state, consisted of renewable energy, conventional generation, active demand, electricity price and transmission network. In this paper, the Monte Carlo simulation (MCs) method is applied to generate the set of numerous transmission system scenarios.

The repetitive process of the MCs method is built on the random sampling and statistical analysis. Generally, identifying the PDF of each uncertainty variable (as explained in Section 2) is the initial part, then further step is to attain some random samples via the random number generator (RNG). Consequently, the output values of these variables can be calculated in a deterministic model. For shortening the time consuming computation, a well-known scenario reduction technique [20] is introduced to eliminate the non-essential scenarios.

### 3.2 TRANSCO MPMOTP model

The TRANSCO considered in this model can acquire electricity from differing types of energy resources, including wind units, PV units and fossil-oriented conventional generation units. Three objectives are emphasized in this proposed MPMOTP model. The maximum benefit of the social $CO_2$ reduction is pursued as the first objective, shown as $O_{cr}$ in (13). In order to minimize the operation costs, the TRANSCO has to make a decision on composing the energy volumes purchased from various resources, as well as the network investment for suiting the liability of power transmission. This goal is treated as the second objective and denoted as $O_{pp}$ in (14). The third objective is to maximize the profit from the demand-side consumption, which is consisted of the positive electricity selling revenue and the negative load shedding penalty, formulated as $O_{rd}$ in (15).

minimize

$$O_{cr} = \rho^{CO_2} \sum_{\omega} \sum_{t} \left[ \sum_{g} P_{gt\omega} \xi_g - \left( \sum_{w} P_{wt\omega} + \sum_{s} P_{st\omega} \right) \xi_{se}^{Av} \right] \eta_{\omega} \tag{13}$$

$$\begin{aligned} O_{pp} = \sum_{\omega} \sum_{t} \Bigg[ & \sum_{w} \lambda_{wt\omega}^{Wind} P_{wt\omega} + \sum_{s} \lambda_{st\omega}^{PV} P_{st\omega} \\ & + \sum_{g} \lambda_{gt\omega}^{CG} P_{gt\omega} + \sum_{\ell} \lambda_{\ell t\omega}^{Line} P_{\ell t\omega} \Bigg] \eta_{\omega} \end{aligned} \tag{14}$$

$$O_{rd} = \sum_{\omega} \sum_{t} \sum_{i} \left( \lambda_{it\omega}^{LS} P_{dit\omega}^{LS} - \lambda_{it\omega} P_{dit\omega} \right) \eta_{\omega} \tag{15}$$

s.t.

$$\sum_{w \in i} P_{wt\omega} + \sum_{s \in i} P_{st\omega} + \sum_{g \in i} P_{gt\omega} - P_{dit\omega} = \sum_{ij, j \neq i} P_{ijt\omega}, \quad \forall i, t, \omega \tag{16}$$

$$P_{ijt\omega} = \frac{\theta_{it\omega} - \theta_{jt\omega}}{x_{ij}}, \quad \forall\, i, j, t, \omega \tag{17}$$

$$-P_{ijt\omega}^{\min} \le P_{ijt\omega} \le P_{ijt\omega}^{\max}, \quad \forall i, j, t, \omega \tag{18}$$

$$P_{wt\omega}^{Wind,\min} \le P_{wt\omega} \le P_{wt\omega}^{Wind,\max}, \quad \forall w, t, \omega \tag{19}$$

$$P_{st\omega}^{PV,\min} \le P_{st\omega} \le P_{st\omega}^{PV,\max}, \quad \forall s, t, \omega \tag{20}$$

$$P_{gt\omega}^{CG,\min} \le P_{gt\omega} \le P_{gt\omega}^{CG,\max}, \quad \forall g, t, \omega \tag{21}$$

$$0 \le P_{dit\omega} \le P_{dit\omega}^{\max}, \quad \forall i, t, \omega \tag{22}$$

$$0 \le P_{dit\omega}^{LS} \le P_{dit\omega}, \quad \forall i, t, \omega \tag{23}$$

$$-\pi \le \theta_{it\omega} \le \pi, \quad \forall i, t, \omega \tag{24}$$

where $t$ is the indices of time periods within the set $T$; $\omega$ is the index of possible scenarios set $\Omega$ generated by MCs; $\eta_{\omega}$ is the occurrence probability of the scenario $\omega$; $i, j, w, s, g$ are the index or indices of the mapping of the bus set $B$ with the wind unit set $W$, the PV unit set $S$ and the conventional power unit set $G$, i.e. $i, j \in B$, $w \in W$, $s \in S$, $g \in G$, where $\{W, S, G\} \subseteq B$; $P_{wt\omega}$, $P_{st\omega}$, and $P_{gt\omega}$ are the purchased power from wind units, PV units and conventional generation units corresponding to the individual marginal price of $\lambda_{wt\omega}^{Wind}$, $\lambda_{st\omega}^{PV}$ and $\lambda_{gt\omega}^{CG}$; $\xi_g$ is the carbon intensity of each type of the fossil-based generation unit, while $\xi_{se}^{Av}$ is the average value of the whole society involved carbon emission intensity; $\rho^{CO_2}$ is the carbon emission tariff; $P_{\ell t\omega}$ is the nominated expansion capacity of the transmission lines with the marginal price $\lambda_{\ell t\omega}^{Line}$ for each possible scenario, and the term $\sum_{l} \lambda_{\ell t\omega}^{Line} P_{\ell t\omega}$ represents the TRANSCO investment cost, correspondingly; $P_{dit\omega}$ is the load at bus $i$, while $P_{dit\omega}^{LS}$ is the potential load shedding with the penalty price $\lambda_{it\omega}^{LS}$; $P_{ijt\omega}$ is the power flow through the line $i$-$j$; $\theta_{it\omega}$ is the voltage phase angle at $i^{\text{th}}$ bus.

In this MPMOTP model, the DC optimal power flow (OPF) is used for the specific intention on various sources of uncertainty in the transmission level, equations (16) guarantee the power balance at each bus. Equations (17) enforce the power flowing through the line $i$-$j$, and further impose the capacity limits in (18). Constraints (19), (20) and (21) limit the production of the wind power, PV power and conventional generation unit within the particular maximum and minimum values, respectively. Likewise, the constraints (22) ensure the demand of each bus is bounded in the individual upper limit. Constraints (23) imply the capacity of the possible load shedding at $i^{\text{th}}$ bus is limited to the actual demand $P_{dit\omega}$. Constraints (24) set the voltage angle bounds for each bus.

## 4 Methodology

In this section, the well-developed two-phase MOPSO algorithm is introduced to properly handle the proposed MPMOTP model, since it is a non-convex nonlinear mixed integer problem associated with the uncertainties' penetration.

### 4.1 PSO algorithm

In general, the particle swarm optimization (PSO) algorithm [21] is a population-based self-adaptive method sorted as one of the heuristic methods. Incorporating with the components of particle and swarm, PSO encourages the local and global exploration of the problem space to obtain better convergence, in which a particle denotes the potential optimal solution and a swarm contains a set of particles. Each particle moves towards a multiple dimensions space to seek a possible solution experienced by the decisions of itself and its neighbors. In the searching space, the searching route of a particle can be recognized as the velocity ($m$) and position ($n$). The updating rule of PSO will steer the particle swarm to gather in a more promising area with better objective value.

### 4.2 Two-phase MOPSO schema

The primary aim of MOPSO is to find an optimal tradeoff between several competing objectives for which usually no single optimal solution exists that minimizes all objective function values simultaneously.

To illustrate the MOPSO algorithm served for the proposed TRANSCO MPMOTP model, in each scenario $\omega$ of a specified time period $t$, the complex cumulative model can be solved as an independent MOTP problem. The pseudo-codes of the MOPSO calculation procedures are shown in Fig. 1, in which archive set $A$ is the vital feature for storing a better Pareto front approaching the optimal solution and hanging out the particles with the best global positions.

Further developed in [22], a two-phase MOPSO schema is proposed in the optimization process which can notably balance the convergence speed and solution diversity. In the first phase, the Sigma method [21] is dedicated to accelerate the convergence and obtain an approximated Pareto front, then an ideal optimal particle method [22] is contributed to facilitate the diversity of the solution in the second phase. The compiling keynotes of the two-phase MOPSO method are specifically indicated in Fig. 2.

### 4.3 MPMOTP planning implementation

In order to indicate the application of the two-phase MOPSO-based programming for solving the proposed MPMOTP model, the illustrative flow chart is shown in Fig. 3. Due to the MOPSO algorithm is essentially a non-constrained heuristic method, for evading the constraint violations, the possible calculation risks coupling with the constraints (16)–(24) are handled by a traditional scheme [22]. In addition, a mutation operator is performed for keeping the efficiency of the Pareto front. Considering a bunch of solutions obtained from the multi-objective problem, but none of them occupy a priority to the others, therefore, a fuzzy decision making approach [23] is taken to select the final solution.

## 5 Case study

The proposed uncertainty-averse MPMOTP model is applied to the IEEE 24-bus test system for a long term planning of continuous 15 years with the interval of 5 years, i.e. three periods. The initial network data can be found in [24]. 41 candidate lines are occupied for this

**P1**: Initialize the swarm $\psi$ (size $\hbar$) in searching space, and the PSO coefficients $\varpi$, $c_1$ and $c_2$ [18], maximum iterations $\Upsilon$, and iteration $\tau$=0. Set the position and velocity of each particle randomly in $\psi$;

**P2**: Decode the particles to obtain the *networks* and calculate the objective functions (13a)-(13c);

**P3**: Find the initial non-dominated solutions and store them in archive $A$;

**P4**: For $p$th particle in $\tau$=1,2,…,$\hbar$

- **P4.1**: Select the global best position $p_{gp}^{\tau}$ from the archive $A$ refer to the solution's diversity;
- **P4.2**: Update position and velocity of each particle according to [21]

$$m_{pq}^{\tau+1} = \varpi \cdot m_{pq}^{\tau} + c_1 \cdot r_1 \cdot \left(p_{pq}^{\tau} - n_{pq}^{\tau}\right) + c_2 \cdot r_2 \cdot \left(p_{gp}^{\tau} - n_{pq}^{\tau}\right)$$
$$n_{pq}^{\tau+1} = n_{pq}^{\tau} + m_{pq}^{\tau}$$

- **P4.3**: Decode the particles to get the network structure and calculate the objective functions (13a)-(13c);
- **P4.4**: Retain the particles within the search space in case they go beyond their boundaries. *If the particle position moves beyond its boundaries, the value of its corresponding boundary will be taken*;
- **P4.5**: Update the local best position $p_{pq}^{\tau}$, *if the current location is dominated by its local best location, then the previous location is maintained, otherwise, the current location is set as the personal best location. If the particles are mutually non-dominated, one particle is selected randomly*;
- **P4.6**: Update the archive $A$ to store the non-dominated solutions from a combined population of the swarm and the archive.
- **P4.7**: Iteration $\tau$+1.

**P5**: Archive $A$ contains optimal solutions for this MOTP problem.

**Fig. 1** Pseudo-codes of the MOPSO calculation procedures for an independent MOTP

**K1**: Apply the Sigma method to facilitate the convergence and obtain a rough Pareto front;

**K2**: Update a set of potential global best positions in each iteration $\tau$ using the available non-dominated solutions in archive $A$;

**K3**: Gain the corresponding particle $p_{pq}^{\tau}$. If $f_z^*$ is the previous optimal value of the $z$th objective;

**K4**: Promote the diversity of the solution with ideal optimal particle method. For a multi-objective optimization problem, the ideal optimal particle $p_{pq}^{\tau,*}$ is decided by

$$\min \phi\left(f\left(p_{pq}^{\tau,*}\right)\right) = \sqrt{\sum_{z=1}^{Z}\left(f_z\left(p_{pq}^{\tau,*}\right) - f_z^*\right)^2}$$

**K5**: Output the global best position $p_{gq}^{\tau,*}$ (the optimal value for each objective) according to the ideal optimal particle $p_{pq}^{\tau,*}$.

**Fig. 2** Keynotes of the two-phase MOPSO method

system, and the new added lines remain the same parameters as described in [24]. The active power limit of each transmission line is set to 170 MW. For each bus, the expected natural growth rate of the connected generator or load is assumed to be 25% per 5-year. The parameters of the two-phase MOPSO are indicated in Table 1, the physical parameters of wind and PV unit are summarized in Table 2, and the economic assumptions of carbon emission tariff and energy purchase price are described in Table 3.

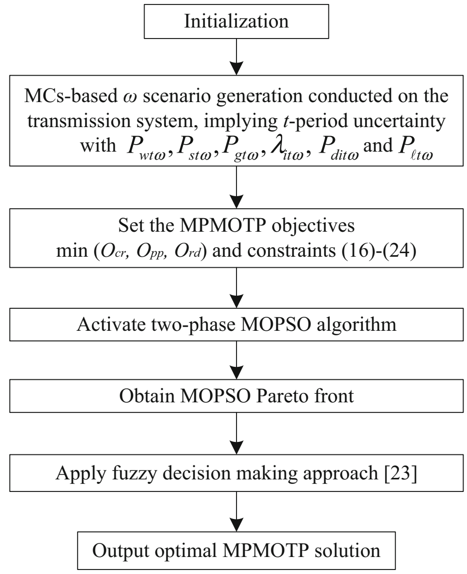


**Fig. 3** Flowchart of the proposed MPMOTP model

**Table 1** The parameters of the two-phase MOPSO

| MOPSO | Parameters |
|---|---|
| Swarm size | $\hbar = 160$ |
| Coefficient | $\varpi = 0.9,\ c_1 = 2.2,\ c_2 = 3.0,\ r_1 = 0.6,\ r_2 = 0.8$ |
| Iteration | $\Upsilon = 100$ |

Referring to [16], the clustered inter-dependency of the uncertainties $P_{wt\omega}$, $P_{st\omega}$, $P_{gt\omega}$, $\lambda_{it\omega}$, $P_{dit\omega}$ and $P_{\ell t\omega}$ is reflected in the coefficient matrix $\boldsymbol{C}$, and imposed as the same formula for simplicity at each bus,

$$\begin{array}{c} P_{wt\omega} \\ P_{st\omega} \\ P_{gt\omega} \\ \lambda_{it\omega} \\ P_{dit\omega} \\ P_{\ell t\omega} \end{array} \begin{bmatrix} 1 & 0.021 & 0.011 & 0.278 & -0.292 & 0.048 \\ 0.021 & 1 & 0.019 & 0.386 & -0.352 & 0.027 \\ 0.011 & 0.019 & 1 & 0.576 & -0.125 & 0.133 \\ 0.278 & 0.386 & 0.576 & 1 & -0.863 & 0.001 \\ -0.292 & -0.352 & -0.125 & -0.863 & 1 & 0.896 \\ 0.048 & 0.027 & 0.133 & 0.001 & 0.896 & 1 \end{bmatrix}$$

To illustrate the effectiveness and adaptability of this proposed TRANSCO planning model, differing conditions should be compiled into the test system, therefore, three case studies are concluded in this section. Case 1 is assumed that no renewable energy unit is explored in this system, only conventional units are devoted into expansion process. In Case 2, for simulating the impacts of the wind and PV units, a 240 MW wind farm and a 160 MW PV

**Table 2** The physical parameters of wind and PV unit

| Type | Parameters |
|---|---|
| Wind unit | $V_{ci} = 4$ m/s, $V_r = 15$ m/s, $V_{co} = 22$ m/s<br>$k = 2$, $c = 5.5$ |
| PV unit | $R_r = 1$ kW/m$^2$<br>$\alpha = 1.8$, $\beta = 4.5$ |

**Table 3** The economic parameters of energy and $CO_2$ emission

| Factors | Parameters |
|---|---|
| $CO_2$ emission | $\xi_g = 0.85$ Ton/MW, $\xi_{se}^{Av} = 0.38$ Ton/MW,<br>$\rho^{CO_2} = 20$ \$/Ton |
| Load shedding | $\lambda_{it\omega}^{LS} = 900$ \$/MW |
| Energy purchase | $\lambda_{wt\omega}^{Wind} = 150$ \$/MW, $\lambda_{st\omega}^{PV} = 200$ \$/MW,<br>$\lambda_{gt\omega}^{CG} = 350$ \$/MW, $\lambda_{lt\omega}^{Line} = 450$ \$/MW |

plant are considered to connect with bus 3 and 7 and increased by 30% per period, respectively. Emphasis on performing the critical penetration of wind and PV energy, in Case 3, two-times capacity is assumed to inject into the same buses with 60% growth rate for each period. The simulation results are conducted in Table 4, in which $C_{inv}$ represents the investment cost of network expansion.

The planning schemes of the Case 1 concentrate on covering the uncertainty of the conventional generation growth to meet the demand variety, the significant investment of network persists in every planning period. The high fossil reliance inspires a high $CO_2$ charge versus the social expect of reducing the $CO_2$ emission, also causes an incremented price burden to the consumer (e.g. 2672.37 k\$ in the 3rd period), while the net income of the TRANSCO is increasing slowly from 60.15 k\$ (1st period) to 185.26 k\$ (3rd period).

Regarding the same situation for Case 2 and 3, on preliminary planning stages, the striking point is that a higher expenditure on energy purchase and branch update is visible to enhance the network more tightly to mitigate the plenty uncertainties mentioned in Section 2. However, according to the remarkable amount of wind and PV energy integration, the goal of social $CO_2$ elimination is achieved. Highlighted in the 3rd period of Case 3, the embedding capacity of renewable energy has touched upon 2048.00 MW, approximately dominating half of the energy supply (4334.49 MW). Comparing with Case 1, the decrement of $CO_2$ reduction relieves a notable social benefit (15.53 k\$), it can be also observed that, starting from the 2nd period, the TRANSCO cost of energy stocking and network reinforcement is fairly decreased in Case 2 and 3. Further observation is that, not only as an uncertainty bearer, but as a beneficiary, accommodating huge quantity of renewable energy can facilitate the TRANSCO to stabilize the investment expectations and hedge the business risks, e.g. in the 3rd period of Case 3, the net profit is growing dramatically to 737.69 k\$.

Moreover, results from the deterministic investment minimization transmission planning (IMTP) model without considering uncertainties are presented in Table 5. The single objective is to minimize $C_{inv}$, while the load, wind and PV output, conventional generation, as well as the LMPs are assumed to be fixed according to the predicted value. Comparing with the MPMOTP schemes (shown in Table 4), for each case, the TRANSCO investment increases significantly period by period, new lines are

**Table 4** The MPMOTP planning schemes for various cases

| Planning | | 1st 5-year | 2nd 5-year | 3rd 5-year |
|---|---|---|---|---|
| Case 1 | Schemes | 1–5(1), 14–16(1) | 6–10(1), 12–23(1), 15–21(1) | 6–7(1), 7–8(1), 6–10(1), 15–24(1) |
| | $O_{cr}$(k\$) | 56.28 | 77.13 | 89.61 |
| | $O_{pp}$(k\$) | 1325.27 | 1864.53 | 2487.11 |
| | $O_{rd}$(k\$) | 1385.42 | 1977.45 | 2672.37 |
| | $C_{inv}$(k\$) | 208.52 | 595.47 | 1072.01 |
| Case 2 | Schemes | 1–5(1), 7–8(1), 14–16(1) | 3–11(1), 6–7(1), 10–12(1) | 3–8(1), 5–10(1), 6–10(1) |
| | $O_{cr}$(k\$) | 51.58 | 71.34 | 83.51 |
| | $O_{pp}$(k\$) | 1372.98 | 1527.58 | 1895.42 |
| | $O_{rd}$(k\$) | 1391.56 | 1803.17 | 2366.72 |
| | $C_{inv}$(k\$) | 539.64 | 613.74 | 658.14 |
| Case 3 | Schemes | 1–5(1), 3–11(1), 7–8(1), 14–16(1) | 3–8(1), 6–7(1), 16–17(1) | 4–5(1), 6–10(1), 17–18(1) |
| | $O_{cr}$(k\$) | 49.87 | 68.34 | 74.08 |
| | $O_{pp}$(k\$) | 1401.95 | 1378.56 | 1458.16 |
| | $O_{rd}$(k\$) | 1417.82 | 1751.38 | 2195.85 |
| | $C_{inv}$(k\$) | 945.73 | 635.27 | 647.52 |

**Table 5** The IMTP planning schemes for each case

| Planning | | 1st 5-year | 2nd 5-year | 3rd 5-year |
|---|---|---|---|---|
| Case 1 | Schemes | 1–5(1), 14–16(1) | 7–8(1), 12–23(1), 15–21(1) | 6–7(1), 7–8(1), 16–17(1), 15–24(1) |
| | $C_{inv}$(k$) | 185.08 | 559.20 | 927.11 |
| Case 2 | Schemes | 1–5(1), 14–16(1) | 7–8(1), 10–12(1), 14–16(1) | 3–8(1), 6–2(1), 7–8(1), 6–10(1) |
| | $O_{rd}$(k$) | 279.56 | 611.23 | 971.14 |
| Case 3 | Schemes | 1–5(1), 14–16(1), 3–8(1) | 6–7(1), 6–10(1), 14–16(1) | 3–8(1), 6–10(1), 16–17(1), 17–18(1) |
| | $O_{rd}$(k$) | 452.91 | 655.33 | 1095.06 |

added to cope with overload lines, but can not clearly perform the effects of the variability in production of wind and PV units.

Particularly in Case 1, ignoring the wind and PV penetration, the periodical investment is much lesser than MPMOTP plan, respectively declined 23.44, 36.27, and 144.90 k$ for each 5-year. That means the extra amounts are requested as the uncertainty-averse expenses on conventional generation, LMP volatility, demand response, and line availability.

For Case 2 and 3, the TRANSCO investment could not exhibit a specific trend as for three periods. However, concluded from the results of both MPMOTP model and IMTP model, the further observation shows that, the total 15-year investment tends to be an equivalent amount. In Case 2, the MPMOTP 15-year investment is 1811.52 k$, while that is 1861.93 k$ in IMTP. Accordingly, the value is 228.52 and 2203.30 k$, respectively in Case 3. That means, for a long term perspective, if a precise total amount control of investment is allocated, the proposed MPMOTP model can not only handle the heterogeneous uncertainties, but also ensure the robustness of phased investment in the strategic TRANSCO planning process.

## 6 Conclusion

Incorporating the ambition of the $CO_2$ reduction, an uncertainty-averse MPMOTP planning model is proposed to handle the multiple uncertainties from renewable energy, conventional generation, market price, load deviation and network deployment. In this paper, the virtue of uncertainty codependency is evaluated by the correlation coefficient matrix and contributed to optimize three TRANSCO concerned objectives. Associated with an introduced two-phase MOPSO solving algorithm, the proposed model is implemented and applied on the IEEE 24-bus test system. The results show that, considering a variety of uncertain conditions, the released planning schemes can be feasibly and effectively put forward to issue the transmission network with high stable and reliable intention of the TRANSCO.

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